Italian Journal of Engineering Geology and Environment
www.ijege.uniroma1.it

A NEW PERSPECTIVE FOR REGIONAL LANDSLIDE SUSCEPTIBILITY ASSESSMENT

Giacomo TITTI(*), Matteo ANTELMI(**), Francesco FUSCO(**),
Laura LONGONI(**) & Lisa BORGATTI(*)

(*)Alma Mater Studiorum University of Bologna - Department of Civil, Chemical, Environmental and Materials Engineering – Bologna, Italy
(**)Polytechnic of Milan - Department of Civil and Environmental Engineering (DICA)– Milan, Italy
Corresponding authors: matteo.antelmi@polimi.it, francesco.fusco@polimi.it

EXTENDED ABSTRACT

Le frane rappresentano un grave rischio geologico in molti Paesi. In Italia le frane censite sono circa 624.601 (periodo di riferimento 1116-2021) e interessano un'area di quasi 24.000 km^2, pari al 7,9% del territorio nazionale (CNR-IRPI report, 2021). La disponibilità di inventari che descrivano la distribuzione spaziale e temporale delle frane è fondamentale per effettuare analisi di suscettibilità e per la definizione del rischio da frana, che risultano a loro volta essere strumenti necessari sia per la pianificazione del territorio sia per lo studio dell'evoluzione del paesaggio nel tempo. Per il territorio italiano sono presenti diverse mappe di pericolosità e rischio da frana, partendo dalla scala regionale sino a quella nazionale. Questi prodotti sono stati sviluppati grazie alla disponibilità del dataset IFFI, ovvero un inventario di frane realizzato e mantenuto aggiornato nel tempo dall'Istituto ISPRA. Tuttavia, per alcune applicazioni, la reale utilità di questo inventario è piuttosto limitata a causa di una diffusa disomogeneità spaziale e dell'utilizzo di diversi metodi di mappatura e criteri di classificazione.

Nonostante negli ultimi anni l'evoluzione delle tecniche utilizzate per la valutazione della suscettibilità da frana a livello nazionale, come i metodi statistici, numerici o basati sull'intelligenza artificiale (ad esempio le reti neurali), sia stata notevole, i risultati sono ancora limitati a causa della qualità dei dati utilizzati, come quella degli inventari di frane. Oltre all'inventario IFFI a scala nazionale, sono disponibili altri geodatabase a scala locale e regionale, come quelli forniti dai "Distretti idrografici", un'autorità pubblica cui spetta la gestione della pianificazione del territorio nell'ambito della salvaguardia da frane e alluvioni. Tali enti non si occupano di mappare l'intero territorio italiano. Tuttavia, a livello locale, possono produrre un miglioramento in termini di precisione e accuratezza rispetto al dataset nazionale disponibile.

In questo studio viene presentato un approccio innovativo per la valutazione della suscettibilità da frana da una scala locale ad una provinciale, basandosi su inventari di frane a livello regionale. Utilizzando una tecnica data-driven, si propone di allenare un singolo modello su un inventario di frane costituito da una composizione di inventari regionali. Il modello dovrà essere in grado di stimare la suscettibilità da frana in diverse aree di studio nel territorio italiano. L'intera analisi è stata condotta utilizzando lo strumento SRT per Google Earth Engine e il plugin SZ per QGIS ed i dati utilizzati e processati sono disponibili e scaricabili gratuitamente.

Nell'ambito del progetto RETURN (*Multi-Risk sciEnce for resilienT commUnities under a changiNg climate*) facente parte del Piano Nazionale di Ripresa e Resilienza-PNRR, l'approccio precedentemente descritto è stato applicato a due aree di studio caratterizzate in passato da eventi di frana e alluvione. Le due aree risultano differenti da un punto di vista geologico e geomorfologico, ma racchiudono al loro interno una rete di infrastrutture ferroviarie e stradali essenziale per la mobilità interregionale: la prima area è nella Regione Campania e comprende un tratto della rete ferroviaria che collega Napoli a Bari; la seconda area invece è nella Regione delle Marche ed interessa i territori maggiormente colpiti dall'alluvione del 2022.

Nelle aree studio selezionate, l'approccio proposto in questo lavoro è stato messo a confronto con la stima di suscettibilità ottenuta mediante l'approccio più diffuso in letteratura, e quindi, rispetto all'attuale stato dell'arte, il migliore a parità di metodo e dati utilizzati. I risultati mostrano come la combinazione di più inventari di frana anche se non spazialmente connessi tra loro non comporta un degrado significativo della capacità predittiva del modello. Per cui, a parità di metodo e dati, i due approcci sono equiparabili.

Affinché l'approccio proposto possa essere consolidato, verranno effettuati ulteriori approfondimenti in diverse aree studio per poi arrivare all'individuazione delle corrispondenti tratte stradali e ferroviarie più vulnerabili.

IJEGE, Special Issue 1 (2024): 275-283, DOI: 10.4408/IJEGE.2024-01.S-30
E-ISSN 2035-5688 | ISSN 1825-6635 / ©Author(s)

ABSTRACT

Landslides pose a severe geohazard in many countries. The availability of inventories depicting the spatial and temporal distribution of landslides is crucial for assessing landslide susceptibility and risk in territorial planning or investigating landscape evolution. In the case of the Italian territory, several landslide hazard and risk maps were produced ranging from regional to national scale. This was made possible leveraging public domain data of the Italian Landslide Inventory (IFFI project; Trigila *et alii*, 2010), or other geodatabases spanning from local to regional scale. However, the practical utility of this inventory is often limited in many applications due to its spatial inhomogeneity or the use of different mapping methods and classification criteria. Despite the impressive advancements in techniques for assessing natural hazard susceptibility at a national scale over the past years, including statistical models, AI based models (*i.e*. Neural Networks) and others, the results are still limited by the quality of the data used. Specifically, the effectiveness of these models is closely tied to the quality of the landslide inventory utilized. Currently, recent regional landslide inventories could potentially enhance precision and accuracy compared to the national dataset, primarily owing to their finer resolution compared to the IFFI dataset. In this work, we present a new approach to assess landslide susceptibility at local scale, relying on regional landslide inventories. Using a data-driven technique, we propose to train a single model on a landslide inventory consisting of a composition of regional inventories selected to be representative of the national scenario. The weighted model is now capable of predicting landslide susceptibility in any study area across Italy. The entire analysis has been done using the SRT tool for Google Earth Engine and the SZ-plugin for QGIS. All the data used and processed are freely available and downloadable. The proposed approach has been tested in the framework of the PNRR RETURN project. The evaluation was conducted in two specific areas: the first one encompasses a section of the railway connecting Napoli to Bari (southern Italy), while the second focuses on areas impacted by the Marche region 2022 landslide event (central Italy).

Keywords*: flow-like landslides, landslide inventory, susceptibility mapping, Generalized Additive Model.*

INTRODUCTION

Landslides are complex natural phenomena that pose severe geohazards in many countries, occurring in diverse geological, geomorphological, and climatological environments. Thus, understanding the spatial and temporal distribution of landslides is crucial to assess related hazards and to support a comprehensive risk assessment (Grelle *et alii*, 2014; Fusco *et alii*, 2021; Fusco *et alii*, 2023a). It holds also high importance for analyzing landscape evolution and sediment budget on scales ranging from slope to basin (Corti *et alii*, 2023). In Italy about 625,000 landslides have been inventoried (covering about the 8% of the territory; CNR-IRPI report, 2021). The growing of urban settlements has led population settlement in areas at risk, where prediction and prevention actions are nowadays a challenge for geoscientists. In this context, landslide inventories can be used for various purposes, such as: preliminary step for the assessment of landslide susceptibility, hazard and risk. They are valuable for investigating landslide distribution, types and patterns in relation to morphological and geological factors as well as for studying landscape evolution. However, the practical utility of these inventories is often constrained by limited accessibility, spatial inhomogeneity or use of different mapping methods and classification criteria. This condition stands as a significant limitation for studies aimed at landslide susceptibility and risk assessment.

Landslide susceptibility assessment is the most common approach to assess how prone to landsliding a landscape is. Several methods and approaches, both qualitative and quantitative, have been proposed and tested for distributed landslide susceptibility assessment (Reichenbach *et alii*, 2018). Qualitative approaches include heuristic ones, such as geomorphological mapping, analysis of landslide inventories, and susceptibility zoning. Quantitative methods encompass physics-based numerical modelling and statistically based classification methods (Guzzetti *et alii*, 1998). At the slope or basin scale this is commonly achieved by applying quantitative methods, such as physics-based models, which consider dynamic variables that illustrate how landslide triggering is significantly affected by hillslope hydrological and morphological conditions, as well as stratigraphic setting of the involved terrains (Ozturk *et alii*, 2016; Tufano *et alii*, 2016; De Vita *et alii*, 2018; Formetta *et alii*, 2019; Panzeri *et alii*, 2022; Sepe *et alii*, 2023). In contrast, for broader geographic contexts, ranging from catchments to regional and even continental scales, landslide susceptibility is commonly generated using expert-driven (Günther *at alii*, 2014) or data-driven (e.g., Ciurleo *et alii*, 2017; Lombardo *et alii*, 2020; Titti *et alii*, 2021a; Ahmed *et alii*, 2023) methods. Expert-driven models involve standardizing and weighting causative factor maps, even in the absence of a sufficiently complete landslide inventory. Data-driven methods can use binary classifiers, originating from statistical or machine learning approaches. Regardless of the specific algorithm at hand, a data-driven-based susceptibility assessment requires a series of spatially-explicit instances describing previously occurred landslides.

Assuming that "*the past is the key to the future*" (Carrara *et alii*, 1995), the model learns how to distinguish the presence from the absence of a landslide based on a set of predisposing factors (*i.e.* slope degree, curvature, aspect, geology). For example, Titti *et alii* (2021) investigated how landslide presence variation affects the model performance by systematically reducing the number of the landslides in the dataset. The model performance has significantly improved in the last decade, particularly with the emergence of artificial intelligence-based models (Dahal *et alii*, 2023), especially when the scale of the analysis is relatively small. However, landslide inventories still face limitations in terms of updating and accuracy. To this regard, is there a method to enhance the accuracy and completeness of landslide inventories in Italy?

In the framework of the PNRR RETURN project (Multi-Risk sciEnce for resilienT commUnities undeR a changiNg climate), an alternative approach is introduced wherein the data-driven model is trained using a selection of landslide inventories to evaluate the landslide susceptibility of a third area. This method, known as transfer learning, has been investigated in the literature for purposes other than landslide susceptibility. More recently, the transfer learning approach has been introduced in the field of landslide susceptibility analysis, as evidenced by studies such as Liu *et alii* (2021), Ai *et alii* (2022), and Wang *et ali*i (2022a), which explore various approaches in delineating model source and target datasets.

For example, Zhu *et alii* (2020) proposed unsupervised transfer learning where source and target areas were selected to be adjacent. On the other hand, Wang *et alii* (2022b) compared a single-source transfer benchmark approach with multiple-source transfer benchmarks for non-adjacent study areas. The key difference between single- and multiple-source transfer learning approaches lies in the number of non-adjacent datasets used to train a model: one for single-source and more than one for multiple-source.

Inspired by the work of Wang et alii., we compare a conventional single-source transfer learning method, where the prediction and training areas are contiguous, with a multi-source transfer learning approach that utilizes non-adjacent training areas. Both scenarios include regional and local landslide inventories, obtained from public Authorities or literature, which exhibit greater accuracy than the national landslide inventory (IFFI project, Triglia *et alii*, 2010), the most used in the literature to attempt landslide susceptibility of the entire Italian territory.

The approach is applied to two selected test sites based on availability of detailed landslide inventories and the presence of critical transport infrastructures (railways and national roads) in landslide-prone territories (Fig. 1). Specifically, the first site comprises a sector of the railway connecting Napoli to Bari (Campania region, southern Italy), while the second one includes areas affected by the Marche 2022 flood event (Marche region, central Italy). The model was trained by coupling the datasets from these two regions with the aim to provide a detailed susceptibility analysis on two site-specific locations within each region.

DATA AND METHODS

Study areas

The approach was tested in two areas of the Italian territory (Fig. 1): the Marche region (central Italy, M); and the Campania region (southern Italy, C). Geologically, these areas coincide with the Apennines chain, a fold-and-thrust belt formed during Neogene-Quaternary by the collision of African and European plates. Orogenesis processes characterized by collisional and extensional tectonic phases involved Triassic to Miocene sedimentary successions (Satolli & Calamita, 2008; Vitale & Ciarcia 2018). Pre-, syn-, and post-orogenic lithologies characterize the areas. In detail, central and eastern areas of the Marche region are characterized mainly by flysch deposits (clays, marls, sandstones); while by carbonate deposits (limestones, dolomites) the western one. Similarly, the Campania region is characterized by flysch deposits in the eastern and southern areas; while also by volcanic deposits (ash-fall pyroclastic covers, tuffs and lavas) in the western sector coinciding with the two volcanic districts (Mt. Somma-Vesuvius and Phlegraean Fields) and the surrounding relief. The complex geological-structural setting strongly affects the morphology of the study areas, characterized by slopes, from steep to hilly, valleys, from narrow to wide, and alluvial plains. In such a complex framework, slope instabilities with different kinematics strongly affect the study areas. Consulting the CAHD (Central Apennines Hydrological District) inventory, 7165 landslide events were revealed for the Marche site (out of 22031 in total); while 15125 landslides (out of 51155 in total), from the LaICa (Landslide Inventory of Campania region; Fusco *et alii*, 2023b) were documented for the Campania site. Such events include falls, topples, slides, flows, creeps, and deep-seated gravitational slope deformations (Cruden & Varnes, 1996; Hutchinson *et alii*, 1988). In this study, only flow events were considered.

Susceptibility mapping

Landslide spatial susceptibility is defined as the probability of occurrence of an event according to geo-environmental factors (Brabb, 1985). The analysis was carried out using a data-driven method known as the Generalized Additive Model (GAM), available in the SZ-plugin v2.0 for QGIS (Titti *et alii*, 2022a). This statistical method allows the user to investigate the partial effect of single predisposing factors and to understand their contribution to the final probability. The GAM includes three different kinds of partial effects: linear, non-linear and categorical. Specifically, nine predisposing factors were considered: slope degree, relative relief, vertical curvature, horizontal curvature, northness, eastness, mean daily precipitation, land cover and lithology.

After a preliminary analysis, mean daily precipitation was categorized as linear while the remaining ordinal covariates as non-linear. Land cover and lithology were treated as categorical predisposing factors. The ordinal factors were collected using

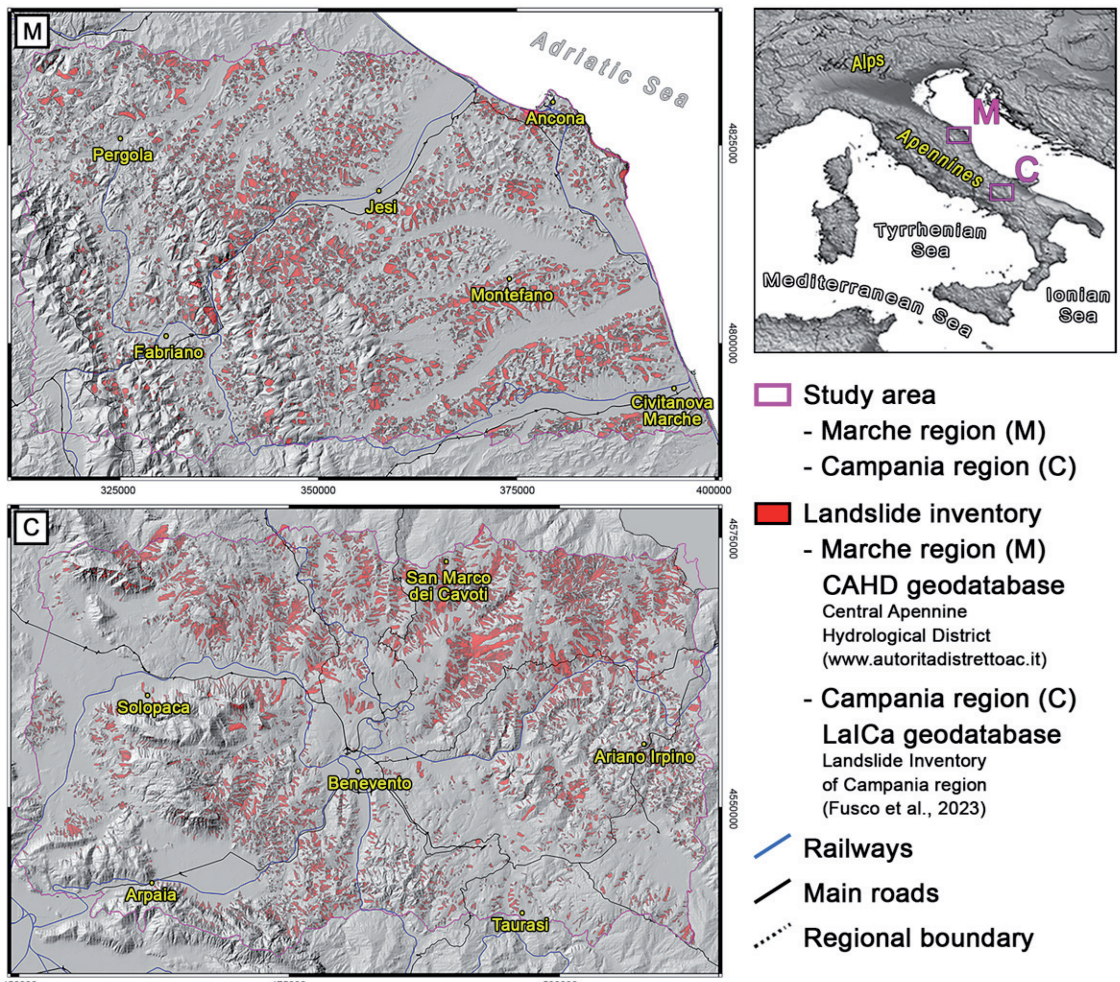

Fig. 1 - Landslide inventory in the Marche (M) and the Campania (C) study areas. (WGS84/UTM 33N)"

the Spatial Reduction Tool (SRT) (Titti *et alii*, 2022) allowing both data retrieval from various sources and spatially reducing of dataset into a mean and a standard deviation representing the single mapping unit. Morphological data were derived from Copernicus DEM (GLO-30) (spacedata.copernicus.eu), rainfall time series from 1991 to 2020 from CHIRPS dataset (chc.ucsb.edu/), land cover from 2018 CORINE land cover (land.copernicus.eu) and lithology from national dataset (portalesgi.isprambiente.it). The relative relief was excluded from the analysis due to its collinearity with the slope. The collinearity between the predisposing factors was evaluated by the Pearson's coefficient. Ultimately, eight covariates were taken into consideration, including six ordinal and two categorical ones. The slope unit subdivision proposed by Alvioli *et alii* (2020) was considered as mapping unit.

To accurately reproduce the statistical distribution of each ordinal covariate in each mapping unit, the mean and standard deviation per ordinal covariate was included in the analysis. A total of 1545 flow-like landslide events in the Marche area and 5334 ones in the Campania area were considered. Furthermore, they were aggregated into 813 and 1208 unstable units, respectively. In total, 4383 slope units in the Marche region and 2543 in the Campania region were selected. The number of flow-like landslide events (flows density) in Marche study area (Fig. 2a, Fig. 2b) is lower than the number in Campania study area (Fig. 2c, Fig. 2d): specifically, 19% and 48% of the selected slope units are unstable, respectively. All the slope units characterizing the Marche dataset (M) and Campania one (C) were sub-sampled in two samples each: M-train (Fig. 2a) and M-trans (Fig. 2b), and C-train (Fig. 2c) and C-trans (Fig. 2d) where 'train' and 'trans' represent the area dedicated to train and to transfer the model knowledge, respectively.

A four steps analysis was carried out, two of those representative of the single-source transfer learning approach (1a and 1b) and two based on the multi-source approach (2a and 2b): 1a) model training

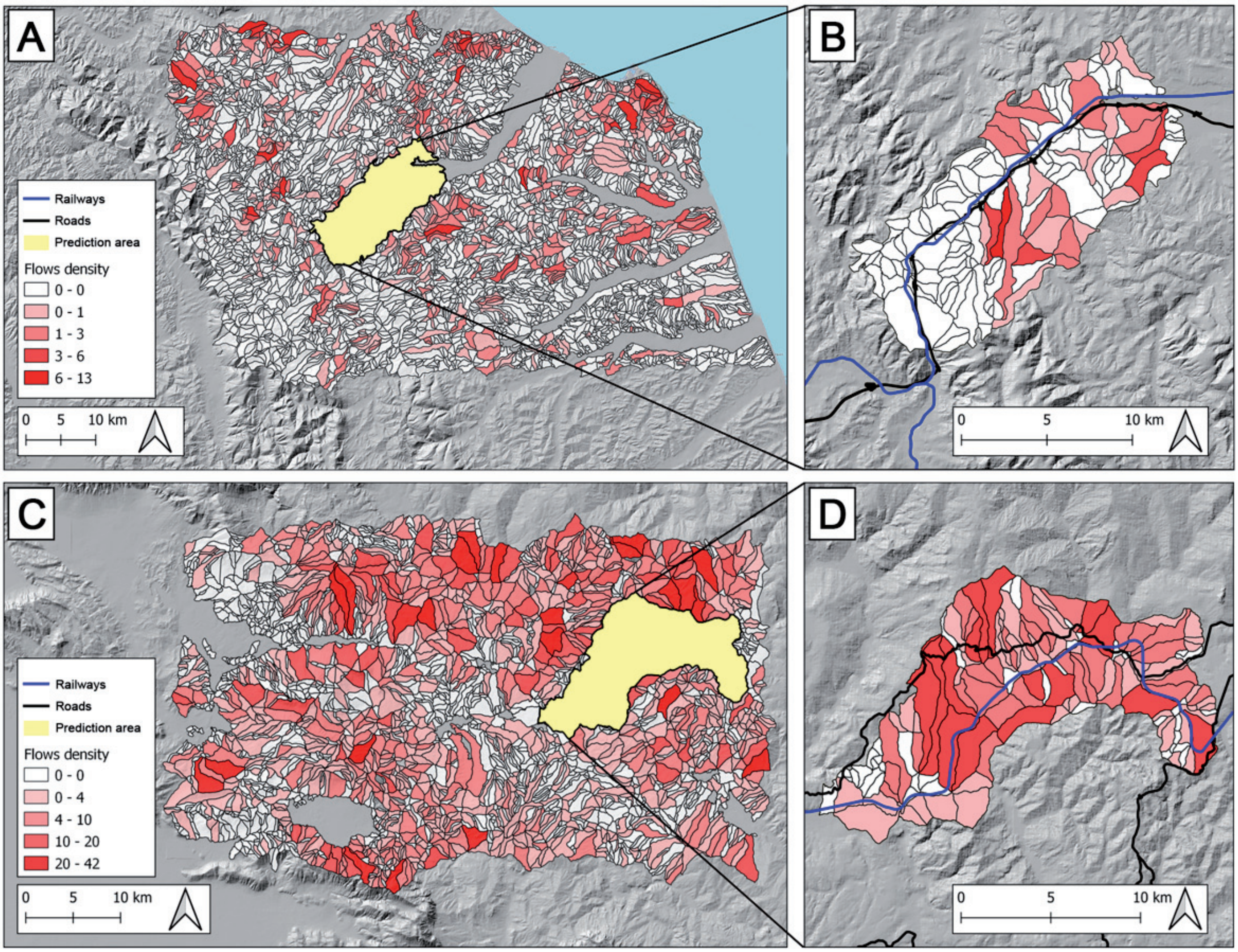

Fig. 2 - Slope units subdivision and flows density (relative number of flow-like landslides) of Marche and Campania study areas. A) M-train study area; B) M-trans study area; C) study area named C-train; D) C-trans study area. (WGS84/UTM 33N)

in M-train area and susceptibility mapping in M-trans; 1b) model training in C-train area and susceptibility mapping in C-trans; 2a) model training in C + M-train areas and susceptibility mapping in M-trans area; 2b) model training in M + C-train areas susceptibility mapping in C-trans. Finally, the resulting maps of steps 1a and 2a and the resulting maps of steps 1b and 2b were compared using several metrics including the Area Under the Receiving Operating Characteristic Curve (AUC) (Fawcett, 2006), the Cohen's Kappa score (Kraemer, 2014), the F1 score (Singhal, 2001) and the confusion matrix based on the Youden index (Fluss *et alii*, 2005).

RESULTS AND DISCUSSION

The prediction capability of the latest generation of data-driven models used for assessing susceptibility is significantly higher than the actual prediction capability reached by their resulting maps due to the limitations induced by inaccuracy of inventories. Accordingly, we attempted to enhance the accuracy and the completeness of the landslide inventory used to train the model. A transfer learning approach to perform susceptibility analysis where landslide inventories are scarce or unavailable is proposed. The aim is in fact to investigate the possibility of training a data-driven model on spatially non-continuous inventories and predict the probability of occurrence where the landslide inventory is missing or limited. Setting the parameters and the conditions above discussed, the model provided the results shown in Fig. 3a for the Marche site (step 1a and 2a). The conventional single-source flow-like landslide susceptibility map of the Marche prediction area (M-trans) was trained on the Marche slope units excluding the slope units of the M-trans area (M-train). Fig. 3b illustrates the multiple-source flow-like landslide susceptibility map of the M-trans area, trained over the M-train area plus all the slope units of the Campania site.

The Fig. 4 shows the results of steps 1b and 2b. In particular, the single-source flow-like landslide susceptibility map of the Campania prediction area (C-trans) trained on the Campania study area, excluding the slope units of the C-trans area (C-train), is reported in Fig.4a. The multiple-source susceptibility map trained on the Marche slope units (M) plus the C-train area is depicted in Fig. 4b. A confusion matrix assigns a True or False status to each slope unit based on the presence/absence of a landslide event and a Positive or Negative status if the susceptibility value of the single slope units is higher or lower than a threshold, that we assumed equal to the Youden index. In Fig. 3 and Fig. 4 the confusion matrix classification of the slope units for the Marche and Campania prediction areas is also visible. The remaining metrics used to evaluate the feasibility of the analysis in M- and C-trans are reported in Tab. 1. The model output generated the spatial distribution of landslide susceptibility in the two case studies. The M-trans susceptibility map (Fig. 3a) is characterized by a concentration of high susceptibility values in few slope units, whereas M-train + C (Fig.3b) shows a wider distribution. The most significant differences are visible in the northern part of the study area. Overall, the susceptibility in the Campania prediction area is generally higher compared to the Marche study area, but the spatial behavior is quite similar. Fig. 4a depicts numerous slope units with high susceptibility values, whereas the case in Fig. 4b shows a concentration of high susceptibility values in the northern part of the prediction area. These spatial trends can be described by the residuals shown in Fig. 5. The residuals were calculated as the difference in susceptibility index between the single-source method and the multiple-source approach that we are proposing. The density distribution of the residual in Fig. 5 is quite different between the two study areas. The Marche area shows a narrow distribution characterized by a concentration of density close to the zero value, whereas Campania shows negative residuals with a wide distribution. Therefore, in the Marche study area the multiple-source approach overestimates the susceptibility, whereas in Campania the multiple-source approach tends to underestimate the susceptibility. Furthermore, both graphs exhibit sign inversions in several slope units. These sign inversions suggest a lack of coherence in the model prediction. Therefore, we can interpret them as the estimates of the uncertainty in the reliability of the approach, which is equal to 20% for the M-trans and 3% for the C-trans, equivalent to a level of confidence of 80% and 97%, respectively.

The confusion matrices of Fig. 3 and Fig. 4 were plotted using the Youden Index to estimate the optimal probability cutoff. In the Marche prediction area, the number of true positive (TP) slope units is 33, while in the Campania prediction area, it is 95. No significant difference is apparent between the Fig. 3c and 3d, as well as between Fig. 4c and 4d. This result confirms that no real evidence

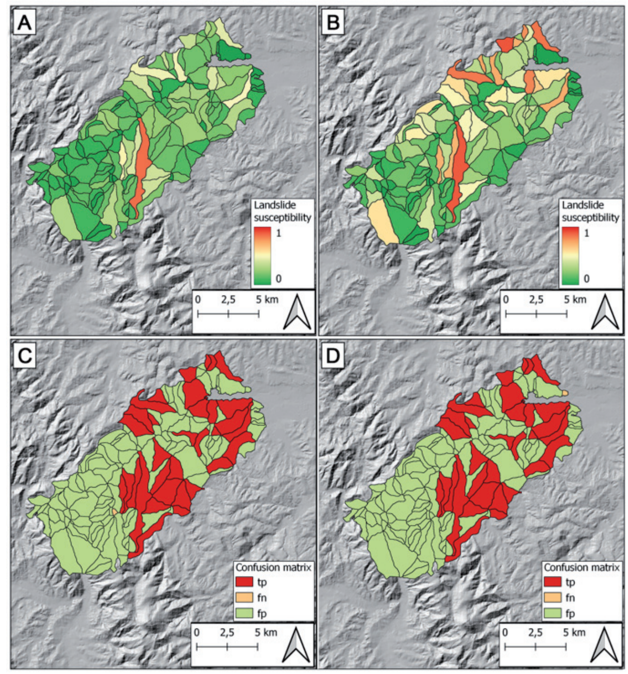

Fig. 3 - Landslide susceptibility maps and relative confusion matrices of Marche prediction area (tp: true positive, fn: false negative, fp: false positive). A) susceptibility map trained on M-train area; B) susceptibility map trained on M-train + C area; C) confusion matrix based on the Youden Index of map A; D) and of map B

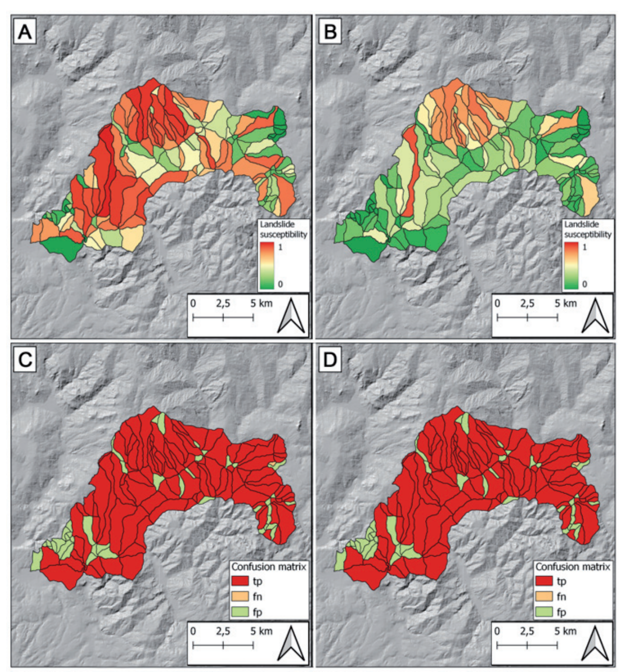

Fig. 4 - Landslide susceptibility maps and relative confusion matrices of Campania prediction area (tp: true positive, fn: false negative, fp: false positive). A) susceptibility map trained on C-train area; B) susceptibility map trained on C-train + M area; C) confusion matrix based on the Youden Index of map A; D) and of map B

of variation in the prediction capacity between the two approaches is apparent, despite the differences observed in the susceptibility maps. The landslide inventories in the prediction areas were used for validating the final map since they did not contribute to training the model. Therefore, the ratio between the unstable slope units and the predicted unstable slope units (true positive plus the false positive units) can be used to assess the validity of the result.

Training area	Prediction area	AUC	Kappa index	F1 score
M-train	Marche (M-trans)	0.85	0.49	0.63
C-train	Campania (C-trans)	0.71	0.36	0.80
C + M-train	Marche (M-trans)	0.80	0.30	0.51
M + C-train	Campania (C-trans)	0.71	0.29	0.65

Tab. 1 - Metrics of predicted susceptibility maps with the model trained on M-train, C-train, C + M -train, M + C-train areas

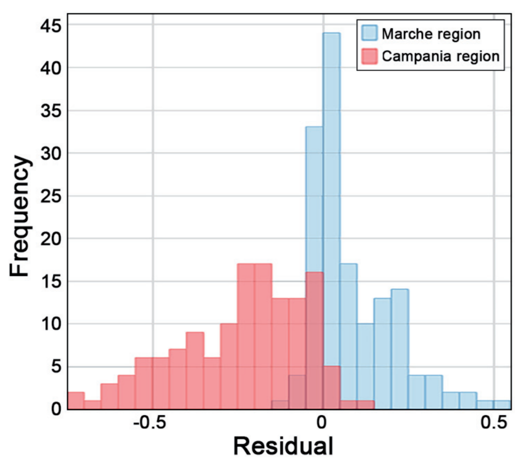

Fig. 5 - Frequency distribution of the residuals in the Marche (blue) and Campania (red) prediction areas calculated as the difference between the susceptibility index of the proposed method and the conventional ones

We cannot validate the results using the stable units, as their past and current stability does not guarantee future stability. Considering the confusion matrices calculated with the Youden index, 100% of the unstable units are still considered unstable in the prediction maps. The maps are deemed valid with an accuracy of 100%. Tab. 1 displays all the numerical metrics calculated for the prediction areas.

Overall, the metrics indicate high values of goodness-of-prediction with minimal differences between the single-source approach and the proposed approach. In general, there are minor differences in the metrics between the analyses conducted in the Campania and Marche regions. These differences can likely be attributed to the significantly higher number of landslide data collected in the Campania region than in the Marche region and to the accuracy in landslide classification and localization method used to create the inventories, which is for the Marche inventory way lower than the one of Campania.

Moreover, the metrics maybe influenced by the prediction area selected. Statistically, the variance of a small population is more variable than in a numerous one, thus, the selection of the prediction area, which have quite small extension in this work, may affect the final result.

CONCLUSIONS

In this study, we introduce a multiple-source approach for mapping landslide susceptibility using a Generalized Additive Model in the absence of a complete or highly accurate landslide inventory. Our proposed method involves training a model on a dataset that is non-adjacent to the prediction area, still ensuring high spatial accuracy. We tested this approach in the Marche and Campania regions by selecting sub-samples from their respective datasets to transfer the weighted model. The susceptibility maps in the prediction areas produced by the proposed approach correctly identified all the unstable mapping units as unstable, thereby validating the maps. Additionally, the prediction capability of all prediction maps, as evaluated by various metrics showed good performance without significant differences between the approaches.

Considering the single-source susceptibility mapping method (*i.e.*, training on X-train and predicting on X-trans) as the baseline, the sign inversion found in the residual analysis could be interpreted as a measure of uncertainty. Overall, the proposed approach exhibits a high level of confidence, with reliability estimated at 80% and 97% for the Marche and Campania prediction areas, respectively. Further analyses will be carried out in other site-specific areas where important linear infrastructures intersect areas affected by numerous landslides phenomena to consolidate the multiple-source approach. The approach will also be extended to different type of landslide affecting the two area with the final aim to produce specific and detailed hazard maps.

ACKNOWLEDGEMENTS

Authors sincerely thank editor and reviewer for providing feedback to improve the manuscript. This study was carried out within the RETURN Extended Partnership and received funding from the European Union Next480 GenerationEU (National Recovery and Resilience Plan – NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1243 2/8/2022, PE0000005).

REFERENCES

Ahmed M., Tanyas H., Huser R., Dahal A., Titti G., Borgatti L., Francioni M. & Lombardo L. (2023) - *Dynamic rainfall-induced landslide susceptibility: a step towards a unified forecasting system.* International Journal of Applied Earth Observation and Geoinformation, **125**: 103593.

Ai X., Sun B. & Chen X. (2022) - *Construction of small sample seismic landslide susceptibility evaluation model based on transfer learning: a case study of Jiuzhaigou earthquake*. B. Eng. Geol. Environ., **81**: 116.

Alvioli M., Guzzetti F. & Marchesini I. (2020) - *Parameter-free delineation of slope units and terrain subdivision of Italy.* Geomorphology, **258**: 107-124.

Brabb E. E. (1985) - *Innovative Approaches to Landslide hazard and Risk Mapping.* International Landslide Symposium Proceedings, Canada, August 23-31, (Japan Landslide Society).

Carrara A., Cardinali M., Guzzetti F. & Reichenbach P. (1995) - *GIS technology in mapping landslide hazard.* Geographical Information Systems in Assessing Natural Hazards; Springer: Dordrecht, The Netherland: 135-175.

Cardinali M., Ardizzone F., Bucci F., Fiorucci F., Pisano L., Santangelo M. & Zumpano V. (2022) - *Geomorphological landslide inventory map of the Daunia Mountains, Southern Italian Apennines.* Earth Syst. Sci. Data, **15**: 753-767.

Ciurleo M., Cascini L. & Calvello M. (2017) - *A Comparison of Statistical and Deterministic Methods for Shallow Landslide Susceptibility Zoning in Clayey Soils.* Eng. Geology **223**: 71-81.

Consiglio Nazionale Delle Ricerche Istituto Di Ricerca Per La Protezione Idrogeologica (2022) - *Rapporto Periodico sul Rischio posto alla Popolazione italiana da Frane e Inondazioni.* Report 2021.

Corti M., Ghirlanda E., Mainetti M., Abbate A., De Vita P., Calcaterra D., Papini M. & Longoni L. (2023) - *Evaluation of the applicability of sediment transport models to dam filling prediction in different Italian geological contexts.* Italian Journal of Engineering Geology and Environment, Special Issue **1**: 27-32.

Cruden D. M. & Varnes D. J. (1996) - *Landslides: Investigation and Mitigation. Chapter 3 - Landslide types and processes*. Transportation Research Board Special Report.

Dahal A. & Lombardo L. (2023) - *Explainable artificial intelligence in geoscience: A glimpse into the future of landslide susceptibility modeling*. Computers & Geosciences, **176**: 105364.

De Vita P., Fusco F., Tufano R. & Cusano D. (2018) - *Seasonal and event-based hydrological response of ash-fall pyroclastic cover in Campania (Southern Italy) for debris flow hazard assessment.* Water, **10**(9): 1140.

Fawcett T. (2006) - *An introduction to ROC analysis.* Pattern recognition letters, **27**(8): 861-874.

Fluss R., Faraggi D. & Reiser B. (2005) - *Estimation of the Youden Index and its associated 732 cutoff point.* Biometrical Journal: Journal of Mathematical Methods in Biosciences, **47**(4): 458-472.

Formetta G. & Capparelli G. (2019) - *Quantifying the three-dimensional effects of anisotropic soil horizons on hillslope hydrology and stability*. J. Hydrol. 2019, **570**: 329-342.

Fusco F., Mirus B.B., Baum R.L., Calcaterra D. & De Vita P. (2021) - *Incorporating the effects of complex soil layering and thickness local variability into distributed landslide susceptibility assessments*. Water **13**: 713.

Fusco F., Abbate A., Calcaterra D., De Vita P., Guerriero L., Longoni L. & Papini M. (2023a) - *Susceptibility mapping of shallow landslides inducing debris flows: a comparison of physics-based approaches.* Italian Journal of Engineering Geology and Environment, **1**: 63-71.

Fusco F., Tufano R., De Vita P. Di Martire D., Di Napoli M., Guerriero L., Mileti F.A., Terribile F. & Calcaterra D. (2023b) - *A revised landslide inventory of the Campania region (Italy).* Sci. Data **10**: 355.

Grelle G., Soriano M., Revellino P., Guerriero L., Anderson M.G., Diambra A., Fiorillo F., Esposito L., Diodato N. & Guadagno F.M. (2014) - *Space-time prediction of rainfall-induced shallow landslides through a combined probabilistic/deterministic approach, optimized for initial water table conditions*. Bulletin of Engineering Geology and the Environment, **73**: 877-890.

Günther A., Hervás J., Eeckhaut M.V.D., Malet J.-P. & Reichenbach P. (2014) - *Synoptic pan-European landslide susceptibility assessment: the ELSUS 1000 v1 map*. Landslide science for a safer geoenvironment. Springer, Cham: 117-122.

Guzzetti F., Carrara A., Cardinali M. & Reichenbach P. (1999) - *Landslide hazard evaluation: A review of current techniques and their application in a multi–scale study, central Italy.* Geomorphology, **31**(1-4): 181-216.

Hutchinson J. N. (1988) - *General report: Morphological and geotechnical parameters of landslides in relation to geology and hydrogeology.* Proc. 5th International Symposium on Landslides, Lausanne, 10-15 July 1988: 3-35.

Kraemer H. C. (2014) - *Kappa coefficient.* Wiley StatsRef: statistics reference online: 1-4.

Lombardo L., Opitz T., Ardizzone F., Guzzetti F. & Huser R. (2020) - *Space-time Landslide Predictive Modelling.* Earth-Science Rev., **209**: 103318.

Ozturk U., Tarakegn Y.A., Longoni L., Brambilla D., Papini M. & Jensen J. (2016) - *A simplified early-warning system for imminent landslide prediction based on failure index fragility curves developed through numerical analysis*. Geomatics, Natural Hazards and Risk, **7**(4): 1406-1425.

Panzeri L., Mondani, M., Taddia G., Papini M. & Longoni L. (2022) - *Analysis of snowmelt as a triggering factor for shallow landslide.* International Multidisciplinary Scientific GeoConference: SGEM, **22**(1.1): 77-83.

Reichenbach P., Rossi M., Malamud B.D., Mihir M. & Guzzetti F. (2018) - *A review of statistically–based landslide susceptibility models.* Earth Sci. Rev, **180**: 60-91.

Rudy A. C. A., Lamoureux S. F., Treitz P. & Van Ewijk K. Y. (2016) - *Transferability of regional permafrost disturbance susceptibility modelling using generalized linear and generalized additive models*. Geomorphology, **264**: 95-108.

Satolli S. & Calamita F. (2008) - *Differences and similarities between the central and the southern Apennines (Italy): Examining the Gran Sasso versus the Matese-Frosolone salients using paleomagnetic, geological, and structural data.* J. Geophys. Res., **113**: B10101.

Sequeira A. M. M., Mellin C., Lozano-Montes H. M., Vanderklift M. A., Babcock R. C., Haywood M. D. E., Meeuwig J. J. & Caley M. J. (2016) - *Transferability of predictive models of coral reef fish species richness*. J. Appl. Ecol., **53**: 64-72.

Sepe C., Calcaterra D., Di Martire D., Fusco F., Tufano R., Vitale E. & Guerriero L. (2023) - *Triggering conditions and propagation of the December 2019 Palma Campania landslide: Implications for residual hazard estimation at recurrent landslide sites.* Eng. Geol., **322**: 107177.

Singha A. (2001) - *Modern information retrieval: A brief overview.* IEEE Data Eng. Bull., **24**(4): 35-43.

Titti G., Napoli G. N., Conoscenti C. & Lombardo L. (2022) - *Cloud-based interactive susceptibility modeling of gully erosion in Google Earth Engine*. International Journal of Applied Earth Observation and Geoinformation, **115**: 103089.

Titti G., Sarretta A., Lombardo L., Crema S., Pasuto A. & Borgatti L. (2022a) - *Mapping susceptibility with open-source tools: a new plugin for QGIS.* Frontiers in Earth Science, **10**: 842425.

Titti G., Van Westen C., Borgatti L., Pasuto A. & Lombardo L. (2021) - *When enough is really enough? On the minimum number of landslides to build reliable susceptibility models.* Geosciences, **11**(11): 469.

Titti G., Borgatti L., Zou Q., Cui P. & Pasuto A. (2021a) - *Landslide Susceptibility in the belt and Road Countries: continental Step of A Multi-Scale Approach.* Environ. Earth Sci, **80**: 1-18.

Trigila A., Iadanza C. & Spizzichino D. (2010) - *Quality assessment of the Italian Landslide Inventory using GIS processing.* Landslides, **7**: 455-470.

Tufano R., Fusco F. & De Vita P. (2016) - *Spatial modeling of ash-fall pyroclastic deposits for the assessment of rainfall thresholds triggering debris flows in the Sarno and Lattari mountains (Campania, southern Italy).* Rend. Online Soc. Geol. It., **41**: 210-213.

Vitale S. & Ciarcia S. (2018) - *Tectono-stratigraphic setting of the Campania region (southern Italy)*. Journal of Maps, **14**(2): 9-21.

Wang H., Wang L. & Zhang L. (2022a) - *Transfer learning improves landslide susceptibility assessment*. Gondwana Research, **117**: 238-254.

Wang Z., Goetz J. & Brenning A. (2022b) - *Transfer learning for landslide susceptibility modeling using domain adaptation and case-based reasoning*. Geoscientific Model Development, **15**(23): 8765-8784.

Wenger S. J. & Olden J. D. (2012) - *Assessing transferability of ecological models: an underappreciated aspect of statistical validation.* Methods Ecol. Evol., **3**: 260-267.

Zhu Q., Chen L., Hu H., Pirasteh S., Li H. & Xie X. (2020) - *Unsupervised feature learning to improve transferability of landslide susceptibility representations*. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **13**: 3917-3930

Received January 2024 - Accepted March 2024